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TDO-MSF: A turn-deviation optimized multi-stage framework for smooth three-dimensional UAV trajectories

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Abstract

Path planning remains a major challenge for the autonomous navigation of Unmanned Aerial Vehicles (UAVs). Despite significant advances in graph-based, sampling-based, metaheuristic, and learning-based path-planning approaches, many existing methods still produce excessive turning points, large path deviations, and trajectories that are misaligned with UAV maneuverability constraints. To address these limitations, this paper presents a Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF) for UAV path planning. The proposed framework integrates a bidirectional A* search algorithm, a turn-deviation reduction strategy, and a direction-constrained neighborhood expansion mechanism to reduce unnecessary directional changes during path generation. A multiscale inflection correction method is employed to eliminate redundant turning points, while a curvature-constrained adaptive-radius smoothing technique is applied to improve trajectory continuity and maneuverability. In addition, a trajectory-guided Enhanced Artificial Potential Field (E-APF) algorithm is incorporated for obstacle avoidance, along with constraints on velocity, acceleration, jerk, and turning radius. The proposed framework is evaluated in various 3D benchmark environments with different obstacle densities and configurations. Its performance is compared with those of the original A*, Improved A*, Improved RRT, Improved PSO, IC-SSA, and the baseline MSF-MTPO algorithms using both conventional path-planning and trajectory-quality metrics. Experimental results indicate that the proposed TDO-MSF achieves an average path-length reduction of approximately 2.08% and a 29.25% reduction in the number of turns compared with the benchmark methods. Furthermore, it improves trajectory smoothness and obstacle-avoidance performance while maintaining curvature-constrained and trajectory-guided obstacle-avoidance capabilities.

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1. Introduction

Unmanned Aerial Vehicle (UAV) technology has become an essential component of many modern applications, including environmental monitoring, precision agriculture, disaster management, surveillance, logistics, smart city development and intelligent military reconnaissance missions [1–5]. The ability of UAVs to operate autonomously in complex three-dimensional environments

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has significantly expanded their practical applications. However, the overall effectiveness of a UAV mission largely depends on the efficiency of its path-planning strategy, which directly influences mission safety, computational efficiency, energy consumption, and operational reliability [6–10]. Graph-search algorithms have been widely employed in engineering optimization and routing problems because of their ability to determine efficient paths under complex constraints. The successful application of Dijkstra-based graph-search algorithms in traffic-flow optimization further demonstrates the effectiveness of deterministic shortest-path strategies for solving complex routing problems [11]. Building on these principles, graph-based algorithms such as A* have become one of the most widely adopted approaches for global UAV path planning because of their computational efficiency, deterministic search capability, and ability to generate near-optimal trajectories [12]. UAV path planning is inherently a multi-objective optimization problem that seeks to simultaneously minimize path length, computational cost, and the number of turning maneuvers while satisfying obstacle avoidance, vehicle dynamic constraints, and environmental requirements. Numerous path-planning algorithms have been proposed, including graph-search methods, sampling-based algorithms, metaheuristic optimization techniques, and learning-based approaches, each offering specific advantages and limitations [13–16]. Among these approaches, the recently proposed MSF-MTPO algorithm combines adaptive neighborhood search, inflection-point correction, and trajectory smoothing to improve path quality and computational efficiency [1]. Although MSF-MTPO effectively reduces redundant nodes and improves the generated trajectory through post-processing, it primarily focuses on path optimization after the initial path has been generated. Consequently, turning behavior and path deviation are not explicitly considered during the search process, which may result in unnecessary inflection points, irregular trajectories, and limited adaptability in complex environments.

Obstacle avoidance remains another significant challenge for autonomous UAV navigation, particularly when unexpected obstacles require rapid trajectory modification. Recent studies have addressed this challenge using metaheuristic optimization, reinforcement learning, hierarchical planning, and cooperative trajectory optimization to improve path quality and navigation performance in complex environments. Although these approaches have demonstrated improved obstacle avoidance and global optimization capabilities, they often suffer from high computational complexity, parameter sensitivity, or limited real-time adaptability, particularly in highly dynamic environments [17–19]. Recent studies have further emphasized that UAV path planning should optimize not only navigation efficiency but also trajectory quality, mission coverage, and operational performance to satisfy practical mission requirements. High-quality trajectories improve mission accuracy, flight reliability, and energy efficiency, particularly in complex three-dimensional environments. In addition, cooperative co-evolutionary optimization with adaptive decision variable selection has been shown to improve search efficiency and coordination for multi-UAV path planning, demonstrating the importance of simultaneously optimizing multiple mission objectives. These findings further highlight the necessity of considering multiple trajectory-quality criteria beyond conventional shortest-path optimization [20–22].

To overcome these limitations, this study proposes a Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF) for UAV path planning. The proposed framework extends the MSF-MTPO algorithm by integrating a turn-deviation-optimized bidirectional A* search that explicitly penalizes unnecessary turning maneuvers and path deviation during node expansion. Furthermore, a multi-scale inflection correction strategy is introduced to improve turning-point detection and reduce waypoint redundancy, while a curvature-constrained adaptive-radius smoothing method generates dynamically feasible trajectories. Finally, a trajectory-guided Enhanced Artificial Potential Field (E-APF) algorithm is incorporated to mitigate local minima and improve obstacle avoidance performance. The effectiveness of the proposed TDO-MSF framework is validated through comprehensive comparative experiments against the original MSF-MTPO algorithm and several state-of-the-art UAV path-planning methods.

1.1. Novel contributions of the proposed TDO-MSF framework

Although numerous UAV path-planning algorithms have been proposed, including graph-search methods, sampling-based algorithms, metaheuristic optimization techniques, and artificial potential field (APF)-based approaches, most existing methods primarily optimize path length while paying limited attention to turning behavior, path deviation, trajectory smoothness and UAV dynamic feasibility. Consequently, the generated trajectories may contain excessive turning maneuvers, redundant inflection points, irregular path geometry, and limited obstacle-avoidance robustness in complex environments. To address these limitations, this study proposes a Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF) for UAV path planning. The proposed framework is developed with the objective of simultaneously improving path optimality, trajectory smoothness, obstacle-avoidance performance and UAV motion feasibility.

Contribution 1: Turn-deviation optimized bidirectional A search.* Conventional bidirectional A* algorithms evaluate nodes primarily using the accumulated path cost and heuristic distance [1]. In contrast, the proposed framework introduces a turn-deviation optimization strategy by incorporating turning-angle and path-deviation penalties into the node evaluation function. As a result, unnecessary direction changes are reduced during the search process, producing smoother and more directionally consistent trajectories.

Contribution 2: Curvature-constrained adaptive radius smoothing. A curvature-constrained adaptive-radius smoothing strategy is developed to generate dynamically feasible UAV trajectories. Unlike conventional trajectory-smoothing approaches based on Bezier curves [23]. The proposed method adaptively adjusts the smoothing radius according to local path geometry and UAV maneuverability constraints, thereby reducing trajectory curvature while preserving path continuity.

Contribution 3: Trajectory-guided enhanced artificial potential field. A trajectory-guided Enhanced Artificial Potential Field (TG-EAPF) is proposed by introducing a guidance potential derived from the globally optimized trajectory. Conventional Artificial Potential Field (APF)-based navigation methods are computationally efficient for obstacle avoidance but often suffer from local minima and trajectory oscillations in complex environments. By incorporating trajectory-guidance information into the potential-field formulation, the proposed TG-EAPF effectively mitigates these limitations while improving obstacle-avoidance performance and trajectory stability. Furthermore, the stability of the proposed guidance strategy is theoretically verified through Lyapunov-based analysis.

Contribution 4: UAV dynamic feasibility verification. To improve practical applicability, UAV dynamic constraints, including velocity, acceleration, jerk, and minimum turning radius, are explicitly incorporated into the trajectory-planning process. In addition, trajectory quality is quantitatively evaluated using average curvature, smoothness index and energy-cost metrics to verify that the generated trajectories satisfy UAV maneuverability requirements.

Collectively, these contributions establish the proposed Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF) as an integrated UAV path-planning framework that simultaneously performs turn optimization, path-deviation minimization, adaptive trajectory smoothing, trajectory-guided obstacle avoidance, and UAV dynamic feasibility verification

2. Literature review

2.1. Graph-based UAV path planning

Many studies have investigated graph-search and sampling-based approaches for UAV navigation because of their ability to generate efficient and collision-free trajectories in complex three-dimensional environments. Traditional graph-search algorithms, including Breadth-First Search (BFS), Depth-First Search (DFS), Dijkstra's algorithm, and A*, construct a graph representation of the environment and expand nodes to determine an optimal route [24]. Sampling-based path-planning methods such as Rapidly-exploring Random Trees (RRT) have also been extensively investigated for three-dimensional UAV navigation. Recent goal-biased RRT algorithms further improve convergence speed and search efficiency by directing tree expansion toward the target, thereby generating feasible collision-free trajectories with reduced exploration time [25]. Several improvements to graph-search methods, including bidirectional search, adaptive heuristic functions, neighborhood optimization, and enhanced node expansion strategies, have been proposed to reduce computational complexity and improve search efficiency [26]. Recent studies have also extended graph-search methods to real-time three-dimensional UAV path planning in uncertain environments, further improving navigation capability while maintaining computational efficiency [27].

However, most graph-based algorithms primarily minimize path length and therefore frequently generate trajectories containing excessive turning maneuvers and redundant inflection points. Moreover, UAV dynamic constraints, trajectory smoothness, and maneuverability are generally considered only during post-processing rather than during the search stage itself. These limitations reduce the practical applicability of conventional graph-search methods for autonomous UAV navigation in complex environments.

Recent studies have further demonstrated that improved A*-based path-planning algorithms can effectively enhance global navigation performance in complex environments by reducing redundant node expansion and improving search efficiency.

2.2. UAV path planning using metaheuristic techniques

Metaheuristic optimization algorithms have been widely adopted for UAV path planning because of their strong global optimization capability and flexibility in solving nonlinear optimization problems [28]. Among recent swarm-intelligence methods, hybrid particle swarm optimization techniques have demonstrated promising performance for cooperative multi-UAV path planning by improving convergence efficiency, maintaining population diversity, and generating higher-quality collision-free trajectories in complex environments [29]. Representative methods include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), Sparrow Search Algorithm (SSA), Dung Beetle Optimization (DBO), and other evolutionary optimization algorithms have demonstrated effective collision-free path generation in complex environments [30]. Recent studies, using multi-strategy fusion, have further improved PSO through the global search capability and solution quality of UAV path planning algorithms [31].

Compared with conventional graph-search methods, metaheuristic algorithms are more suitable for exploring large search spaces and simultaneously optimizing multiple objective functions. Recent survey studies have also highlighted evolutionary computation as one of the most effective optimization paradigms for solving complex UAV path-planning problems because of its flexibility and global search capability [32]. Recent hybrid swarm-intelligence approaches have further demonstrated their effectiveness for multi-UAV path planning in complex environments [33]. However, further improvements are still required to jointly optimize turning behavior, trajectory smoothness, and dynamic feasibility [34]. Recent comprehensive survey studies have further indicated that future UAV path-planning research should integrate multiple mission objectives, communication constraints, and intelligent optimization techniques within a unified framework to address increasingly complex operational environments [35]. Nevertheless, these methods are often highly sensitive to parameter selection and may suffer from premature convergence and unstable optimization performance [36]. Consequently, recent studies have focused on developing multi-strategy optimization frameworks to improve convergence speed, solution quality and robustness for three-dimensional UAV path planning. Because randomness is inherent in population-based optimization, different runs frequently produce different trajectories, and the generated paths do not always satisfy UAV dynamic constraints without additional smoothing procedures. Consequently, although recent optimization algorithms have improved path quality and search efficiency, further research is still required to jointly optimize turning behavior, trajectory smoothness, and UAV motion feasibility

2.3. Research gap and limitations of existing methods

Despite significant advances in UAV path planning, several important challenges remain unresolved. Recent studies have shown that adaptive A*-based algorithms improve search efficiency and path optimality; however, they still generate unnecessary turning maneuvers because of grid discretization and limited consideration of trajectory smoothness [1, 2]. Multi-UAV path-planning methods have further enhanced mission coordination and task allocation, but they introduce additional challenges related to trajectory planning, scalability, and adaptability in complex environments [4, 5]. Several optimization-based approaches have been proposed to improve path quality in complex environments W. Xu *et al*. [9] investigated UAV path planning for bridge inspection in complex terrain, demonstrating effective obstacle avoidance and navigation; however, the proposed method primarily focused on task-specific path generation rather than explicit trajectory-smoothing optimization. Cheng *et al*. [10] developed a hybrid optimization framework that achieved improved path quality; however, the algorithm remained computationally intensive and required careful parameter tuning. Similarly, Li and Han [14] demonstrated that adaptive bidirectional RRT algorithms provide effective global exploration in complex environments; however, the generated trajectories still require additional smoothing before practical deployment. Jenabi *et al*. [15] employed deep reinforcement learning for UAV trajectory optimization; however, the method requires extensive training data and exhibits limited generalization capability in previously unseen environments.

Recent studies have also attempted to improve UAV trajectory optimization through multi-UAV cooperation, hybrid optimization, hierarchical planning, and metaheuristic algorithms. Wang *et al*. [16] investigated multi-UAV trajectory planning but primarily focused on trajectory planning and resource allocation rather than explicit turning-angle minimization and trajectory-smoothing optimization. Nayeem *et al*. [18] proposed a hybrid learning-based optimization approach, although its performance depends on learning convergence and parameter selection. Fan *et al*. [19] developed a hierarchical path-planning framework without explicitly considering turning reduction, whereas Majeed and Hwang [20] developed a multi-objective coverage path-planning algorithm for UAV operations in urban environments; however, the proposed method primarily emphasized coverage optimization and did not explicitly consider turning-angle reduction or trajectory-smoothing optimization. Qi *et al*. [23] developed a Bezier curve-based trajectory planning approach that significantly improves trajectory smoothness for UAV navigation. Nevertheless, the method mainly concentrates on post-processing trajectory optimization and does not explicitly integrate turning-angle minimization or path-deviation optimization into the global path-planning process. Likewise, Zheng *et al*. [24] investigated cooperative optimization for high-dimensional UAV task allocation and trajectory planning, demonstrating improved coordination efficiency. Nevertheless, the proposed approach does not explicitly incorporate turning-angle reduction or path-deviation optimization into the global path-planning process.

Furthermore, Meng *et al*. [37] proposed a cooperative co-evolutionary algorithm with adaptive decision variable selection for multi-UAV path planning, which improved coordination and search efficiency. However, the method primarily focuses on cooperative optimization and does not explicitly optimize turning maneuvers, trajectory smoothness, or UAV dynamic feasibility. Wang *et al*. [38] developed a multi-objective UAV path-planning method based on the Jellyfish Search Algorithm to optimize multiple path-planning objectives. However, the algorithm relies on iterative swarm optimization and does not incorporate curvature-constrained trajectory smoothing or trajectory-guided local obstacle avoidance. Luo *et al*. [39] presented a comprehensive review of unmanned aerial vehicle path-planning techniques, summarizing recent advances and challenges across graph-search, sampling-based, metaheuristic, and learning-based methods. However, the study serves as a survey and does not propose a unified framework for simultaneously optimizing turning reduction, trajectory smoothness, and dynamic flight feasibility. Yang and Wei [40] proposed a hybrid path-planning algorithm that combines an improved A algorithm with an adaptive Dynamic Window Approach (DWA) to enhance navigation performance and obstacle-avoidance capability for autonomous robotic systems. However, the proposed method was developed for ground robots and did not explicitly consider UAV trajectory smoothness or dynamic flight constraints.

Table 1 summarizes the limitations of representative UAV path-planning algorithms across different categories. Although graph-search-based methods generate deterministic solutions, they often produce trajectories containing excessive turning points. Optimization-based methods improve global search capability; however, they are computationally expensive and highly sensitive to parameter tuning. Sampling-based methods, such as Rapidly-exploring Random Tree (RRT)-based algorithms, introduce randomness into the generated trajectories and often require additional post-processing to improve trajectory smoothness and path quality, whereas learning-based methods depend on extensive training datasets and incur high computational costs.

The baseline MSF-MTPO algorithm adopts a multi-stage optimization strategy to improve path quality; however, it remains limited in eliminating redundant inflection points and adapting the smoothing process to different trajectory characteristics. To address these limitations, this study proposes the Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF), which incorporates turn-penalized and deviation-aware path optimization together with adaptive trajectory smoothing. Although the proposed framework introduces a small increase in computational complexity, it provides a better balance among computational efficiency, trajectory smoothness, and navigation safety. Based on the Table 1 analysis, the following research gaps are identified:

Table 1: Deficiencies in existing UAV path planning and TDO-MSF motivation.

Algorithm Category	Representative Methods	Limitations
Graph Search-Based Methods	BFS, DFS, Dijkstra, A*, IDA*	Computational complexity greatly increases with environment size. Efficiency governed by heuristic function design. Often creates paths with too many turns.
Evolutionary & Swarm Optimization Methods	GA, DE, PSO, ACO, GWO, SSA	Prone to premature convergence; require extensive parameter tuning; high computational cost; difficulty maintaining solution stability in complex environments.
Bio-Inspired Optimization Methods	ABC, FA, BA, CS, FSA	Limited performance in high-dimensional or constrained environments; slow convergence speed; sensitive to parameter selection.
Advanced Metaheuristic Methods	DOA, GGO, HO, LPO	High computational overhead; complex parameter configuration; reduced efficiency handling non-linear and dynamic constraints.
Sampling-Based Methods	RRT, RRT*, PRM	Random sampling introduces redundancy; lack of smoothness; requires additional post-processing; optimality depends on large number of iterations.
Local Planning Methods	Local Planning Methods	Prone to local minima; instability in narrow passages; high computational load for dynamic environments; limited global optimality.
Learning-Based Methods	CNN, RNN, DQN, PPO, DDPG	Requires extensive training datasets; strongly influenced by training data characteristics; weak performance outside training environment; computationally intensive.
Imitation Learning Methods	Behavioral cloning, inverse RL	Dependence on expert demonstrations; limited adaptability; high cost of acquiring high-quality training data.
Multi-Stage Path Planning Methods	MSF-MTPO Base Method	Residual redundant inflection points; limited adaptability in smoothing; fixed-radius trajectory optimization restricts flexibility.
Proposed Method	TDO-MSF Framework	Additional computational steps for trajectory optimization; requires tuning of weighting parameters (slight increase in implementation complexity).

1. Current graph-search algorithms do not incorporate turning penalties during the path formation stage.
2. Path deviation is rarely considered during node expansion, resulting in unnecessary trajectory changes.
3. Existing inflection-point correction methods rely on fixed-scale strategies that may fail to eliminate redundant turning points.
4. Most trajectory smoothing methods do not explicitly consider UAV dynamic constraints, such as turning radius and maneuverability.
5. Artificial Potential Field (APF)-based obstacle avoidance methods remain susceptible to local minima and trajectory oscillations.
6. Very few studies simultaneously optimize path length, turning behavior, trajectory smoothness, obstacle avoidance, and UAV dynamic feasibility within a unified framework.

Recent survey studies on autonomous motion-planning algorithms have indicated that modern navigation frameworks increasingly integrate global path planning, local obstacle avoidance, communication constraints, and intelligent optimization techniques to satisfy complex mission requirements. Existing motion-planning algorithms still face challenges in simultaneously achieving path optimality, computational efficiency, trajectory smoothness, and real-time adaptability within a unified framework [41]. Recent hybrid optimization methods have further improved UAV path planning by integrating multiple adaptive search strategies to enhance convergence speed and solution quality. However, these approaches still rely on computationally intensive iterative optimization and do not explicitly integrate turn-aware search, multi-scale trajectory correction, and dynamic-feasibility optimization within a unified path-planning framework [42].

Recent routing optimization studies have demonstrated that graph-search algorithms remain highly effective for shortest-path optimization in complex transportation networks. Nevertheless, these methods primarily focus on route optimization and do not address UAV-specific trajectory requirements such as turning behavior, trajectory smoothness, and flight dynamic constraints [43].

Despite these advances, achieving an effective balance among path optimality, computational efficiency, trajectory smoothness and dynamic feasibility remains an open research challenge.

Therefore, the principal research gap identified in the literature is the lack of an integrated UAV path-planning framework that simultaneously reduces turning behavior, controls path deviation, improves trajectory smoothness, satisfies UAV maneuverability requirements, and maintains robust obstacle-avoidance performance. Recent review studies have similarly concluded that developing unified path-planning frameworks capable of balancing multiple performance objectives remains an important direction for future UAV navigation research [44]. To address this gap, this study proposes the Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF), which integrates turn-penalized bidirectional A* search, deviation-aware optimization, multi-scale inflection correction, adaptive-radius smoothing, and trajectory-guided enhanced artificial potential fields into a unified path-planning framework. The proposed framework aims to generate collision-free, dynamically feasible trajectories with fewer turning maneuvers, improved smoothness and enhanced computational efficiency.

Recent UAV path-planning studies have attempted to improve navigation performance through enhanced Artificial Potential Field (APF) methods and hybrid sampling-based planning algorithms. Improved APF approaches have enhanced obstacle avoidance performance but remain susceptible to local minima and trajectory oscillations in complex environments. Likewise, hybrid sampling-based RRT algorithms have improved global exploration and path generation efficiency for autonomous robotic navigation; however, they often produce irregular trajectories that require additional smoothing and dynamic feasibility optimization before being applied to UAV navigation. [45, 46].

2.4. Artificial potential field-based obstacle avoidance

Artificial Potential Field (APF) methods are widely used for local obstacle avoidance because of their simple mathematical formulation and low computational complexity. In the classical APF model, the destination generates an attractive potential, whereas surrounding obstacles generate repulsive potentials. The UAV trajectory is then determined by the resultant virtual force acting on the vehicle.

Because of their computational efficiency, APF algorithms are frequently integrated with global path-planning algorithms to improve real-time obstacle avoidance. Several enhanced APF variants have also been proposed to reduce trajectory oscillations and improve navigation performance in dynamic environments. Despite these advantages, conventional APF methods remain susceptible to local minima, oscillatory behavior near obstacles, and poor coordination between global path planning and local obstacle avoidance. Consequently, locally generated trajectories may deviate significantly from globally optimal paths, reducing navigation efficiency.

To overcome these limitations, the proposed TDO-MSF framework incorporates a trajectory-guided Enhanced Artificial Potential Field (E-APF), which introduces an additional guidance potential based on the globally optimized trajectory. This strategy improves obstacle avoidance while reducing path deviation, avoiding local minima, and enhancing navigation stability. Therefore, the proposed approach establishes stronger coordination between global path planning and local trajectory optimization than conventional APF-based methods.

3. Proposed TDO-MSF

3.1. Overall framework architecture

The proposed Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF) is designed to generate safe, smooth, and dynamically feasible UAV trajectories in complex three-dimensional environments. Unlike conventional path-planning approaches that perform path optimization and trajectory refinement separately, the proposed framework integrates global path generation, trajectory correction, smoothing, dynamic obstacle avoidance and UAV feasibility verification into a unified architecture.

The overall workflow of the proposed framework consists of five consecutive stages. First, a Turn-Deviation Optimized Bidirectional A* search algorithm generates an initial collision-free path while incorporating turning-angle and path-deviation penalties into the node evaluation function. This helps minimize unnecessary alterations to headings and superfluous maneuvering while searching for the optimal route.

Secondly, the Multi-Scale Inflection Correction technique evaluates the trajectory across multiple neighborhood scales to eliminate redundant inflection points without altering the path's key features.

Thirdly, the Curvature-constrained Adaptive Radius Smoothing approach replaces the sharp bends in the trajectory with arcs. The smoothing radius is adaptively adjusted according to local path geometry and UAV maneuverability constraints to ensure dynamically feasible flight trajectories.

Fourth, a Trajectory-Guided Enhanced Artificial Potential Field (E-APF) is employed for dynamic obstacle avoidance. Adding another guidance potential function helps eliminate issues related to local minima while ensuring the trajectory does not deviate unnecessarily from its optimal path. Last but not least, the trajectory is verified according to the UAV's dynamic constraints in terms of velocity, acceleration, jerk and radius of curvature. Other trajectory-quality metrics, such as average curvature and energy costs, will also be used for verification.

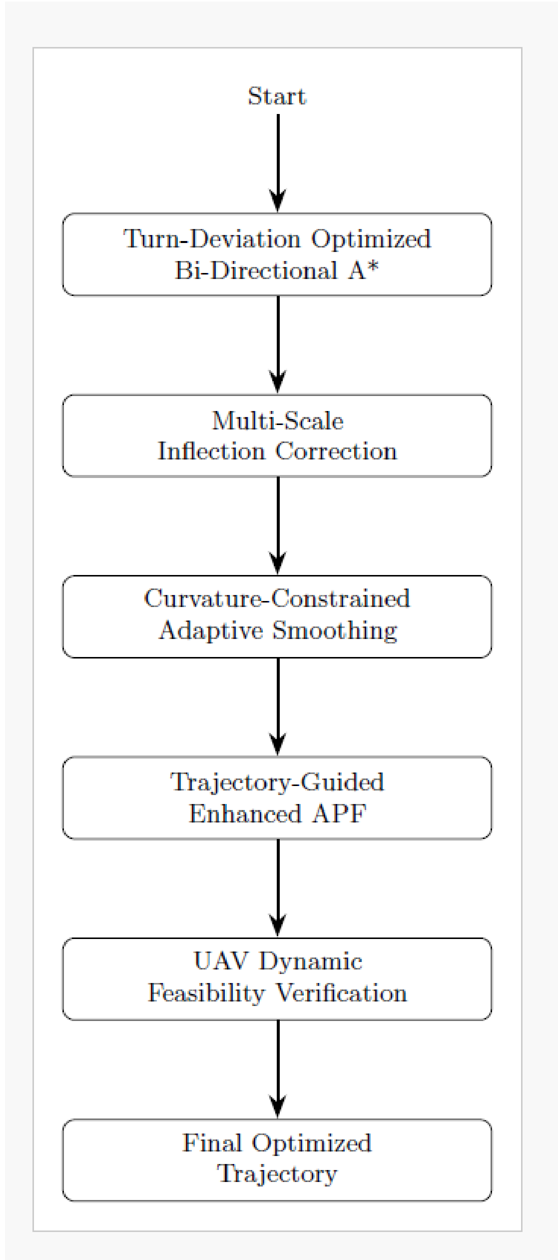

Figure 1: Overall architecture of the proposed TDO-MSF.

3.2. *Algorithm pipeline*

The proposed TDO-MSF algorithm, presented in Algorithm 1, describes the complete computational workflow of the proposed framework. The algorithm begins by initializing the start node, goal node, obstacle information, and the weighting parameters associated with turn and deviation optimization. A Turn-Deviation Optimized Bidirectional A* search is then performed to generate an initial collision-free path by simultaneously expanding the search from both the start and goal nodes while incorporating turning-angle and path-deviation penalties into the node evaluation function.

The generated path is subsequently processed using the Multi-Scale Inflection Correction stage, which removes redundant turning points while preserving the essential geometric characteristics of the trajectory. Next, the Curvature-Constrained Adaptive Radius Smoothing stage replaces sharp corners with curvature-continuous arc segments. The smoothing radius is adaptively determined according to the local path geometry and UAV maneuverability constraints, thereby producing dynamically feasible trajectories.

Following trajectory smoothing, the optimized path is refined using the Trajectory-Guided Enhanced Artificial Potential Field (E-APF). This stage combines attractive, repulsive, and trajectory-guidance potential fields to improve obstacle avoidance while minimizing unnecessary path deviation and reducing the likelihood of local minima.

Algorithm 1: TDO-MSF Algorithm

Input: Start node S, Goal node T, obstacle set Obs, turn penalty weight $\lambda = 50$, deviation penalty weight $\mu = 20$
Output: Dynamically feasible collision-free trajectory P_{final}

Step 1: Turn-Deviation Optimized Bidirectional A* Search;
Initialize $Open_S \leftarrow \{S\}$, $Open_T \leftarrow \{T\}$;
Initialize $Closed_S \leftarrow \emptyset$, $Closed_T \leftarrow \emptyset$;
Construct the direction-constrained neighborhood structure;
while $Open_S \neq \emptyset$ ***and*** $Open_T \neq \emptyset$ **do**
  Select node C minimizing $f(C)$ where $f(C) = g(C) + h(C) + \lambda \sum_i \left(\frac{\theta_i}{180}\right)^2 + \mu D_{\text{dev}}(C)$;
  Apply direction-constrained neighbor selection;
  Expand feasible neighboring nodes;
  Update $g(C)$, $h(C)$, turning penalty, and deviation cost;
  Insert updated nodes into the priority queue;
  Move expanded nodes into the closed sets;
  if *forward and backward searches meet* **then**
    Reconstruct initial path P;
    break;

Step 2: Multi-Scale Inflection Correction;
Initialize corrected path P_1;
for *each waypoint* $p_i \in P$ **do**
  Compute turning angle at p_i;
  Evaluate local geometry at scales $\{3, 5, 7\}$;
  Remove redundant inflection points;
  Preserve safety-critical turning points;

Perform collision verification;
Obtain corrected path P_2;
Step 3: Curvature-Constrained Adaptive Radius Smoothing;
Initialize smoothed path P_{smooth};
for *each waypoint* $p_k \in P_2$ **do**
  Compute turning angle θ;
  Compute adaptive turning radius $r = \dfrac{k\theta}{2\sin(\theta/2)} R_{\min}$;
  Determine the arc center;
  Generate curvature-constrained arc segment;
  Enforce UAV turning-radius constraint;

Step 4: Trajectory-Guided Enhanced Artificial Potential Field;
Compute attractive potential;
Compute repulsive potential;
Compute trajectory-guidance potential;
Compute total potential field;
Compute resultant force;
Update UAV position;
Continue until the target region is reached;
Step 5: UAV Dynamic Feasibility Verification;
Compute velocity profile;
Compute acceleration profile;
Compute jerk profile;
Verify $v_i \leq v_{\max}$ and $a_i \leq a_{\max}$ and $j_i \leq j_{\max}$;
Verify UAV turning-radius constraint;
if *any constraints are violated* **then**
  Refine the smoothing stage;

Step 6: Trajectory Quality Evaluation;
Compute path length;
Compute total turning angle;
Compute obstacle-clearance distance;
Compute average curvature;
Compute smoothness index;
Compute energy cost;
return final optimized trajectory P_{final};

Figure 2: TDO-MSF Algorithm.

The resulting trajectory is then subjected to UAV Dynamic Feasibility Verification, where the velocity, acceleration, jerk, and turning-radius constraints are evaluated. If any dynamic constraint is violated, the trajectory is iteratively refined until all feasibility requirements are satisfied.

Finally, the algorithm evaluates the trajectory using multiple performance metrics, including path length, total turning angle, obstacle-clearance distance, average curvature, smoothness index, and energy cost, before returning the final optimized UAV trajectory.

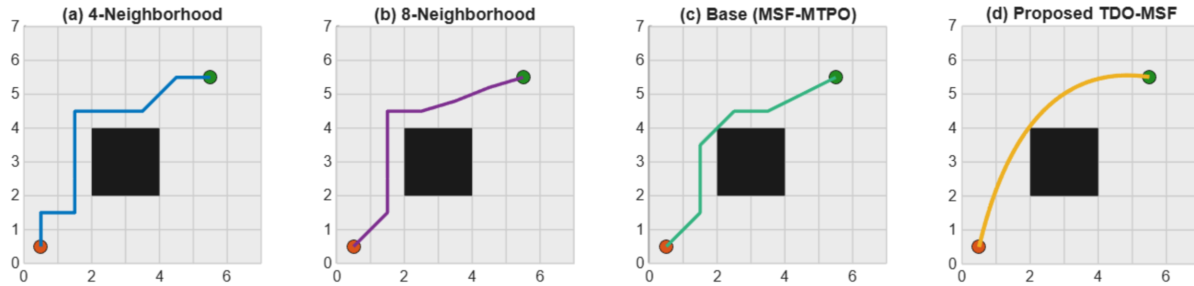

Figure 3: Comparative analysis of neighborhood-based path planning strategies and the proposed TDO-MSF in a grid-based environment.

3.3. Turn-deviation-optimized bidirectional A* search

The first stage of the proposed TDO-MSF is a turn-deviation-optimized bidirectional A* search algorithm. Unlike conventional A*, which evaluates nodes solely by path cost and heuristic distance, the proposed method incorporates turning-angle and path-deviation penalties into the node evaluation function to generate smoother and more efficient UAV trajectories.

The proposed cost function is defined as:

$$f(C) = g(C) + h(C) + \lambda \sum_i \left(\frac{\theta_i}{180}\right)^2 + \mu D_{\text{dev}}(C). \tag{1}$$

The $g(C)$ denotes the accumulated path cost, $h(C)$ is the heuristic cost, θ_i is the turning angle at the i-th node, $D_{\text{dev}}(C)$ indicates the deviation penalty, λ and μ are weighting parameters that balance path length, smoothness and deviation control.

This is accomplished by using a bidirectional search method, which reduces the search space and computational costs. As a result, the global path obtained after the process will be much shorter and will not have any superfluous turnings or bends. Moreover, the use of a bidirectional approach allows the correction of the starting path trajectory. Parameters λ and μ regulate the effects of the turning policy and the deviation value on node exploration.

Unlike conventional A* search, the proposed cost function optimizes the path as the search proceeds. As a result, it reduces unnecessary turns and redundant path deviations while maintaining computational efficiency. The initial path generated by this stage is further refined using the proposed Multi-Scale Inflection Correction method.

Figure 3(a) Using a four-neighborhood search, which allows only movement along the axes, yields a route with many sharp bends and a longer total travel distance. Figure 3(b) displays the eight-neighborhood search, where diagonal moves are allowed, thus producing efficient routes. This approach may still lead to inefficiencies and corner-cutting near obstacles when not appropriately addressed.

The conventional MSF-MTPO algorithm, shown in Figure 3(c), improves efficiency and the smoothness of the resulting route. Nevertheless, the generated route may still deviate, as the per-node cost calculation does not account for turn and deviation coefficients. Figure 3(d), depicts the developed TDO-MSF approach. With the introduction of costs for turns and deviations, together with a flexible approach to path optimization, a smooth path emerges. This approach entails fewer changes in direction and maintains its efficiency while avoiding collisions.

3.3.1. Direction-constrained neighbor expansion

To reduce unnecessary turning behavior and path deviation during the search process, the proposed TDO-MSF adopts a direction-constrained neighbor expansion strategy. Unlike conventional A*, which evaluates all neighboring nodes equally, the proposed method selects candidate nodes based on the current direction of movement and predefined turning constraints. This strategy reduces redundant node expansion and generates smoother trajectories.

Table 2 shows that each direction of motion has a set of candidate neighbors. When expanding nodes, both the turning angle and path deviation are evaluated for each candidate. A candidate node is accepted only if

$$\theta_k \leq \theta_{\max}, \tag{2}$$

and

$$D_{\text{dev}} \leq D_{\text{th}}. \tag{3}$$

Table 2: Direction constrained neighbor selection.

Direction	Candidate set N_d	Turning constraint	Deviation constraint	Accepted move
North-East	{(0, 1), (1, 1), (1, 2)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
East	{(1, 0), (1, 1), (2, 1)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
South-East	{(1, 0), (1, -1), (2, -1)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
South	{(0, -1), (1, -1), (1, -2)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
South-West	{(0, -1), (-1, -1), (-1, -2)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
West	{(-1, 0), (-1, -1), (-2, -1)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
North-West	{(-1, 0), (-1, 1), (-2, 1)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*
North	{(0, 1), (-1, 1), (-1, 2)}	θk ≤ θmax,	Ddev ≤ Dth	(x, y) + d*

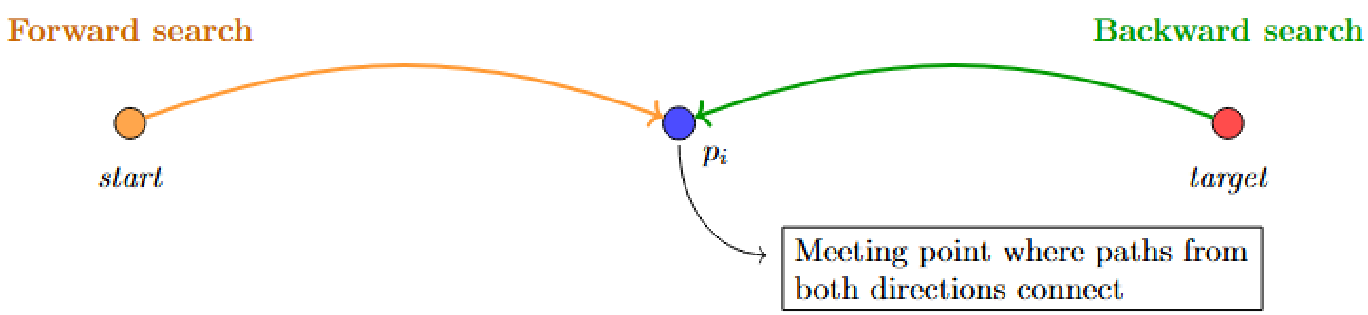

Figure 4: Penalized bidirectional motion trajectory.

In this case, the choice of the movement direction will be made based on the best direction available. By limiting the search space through directional constraints, the method proposed in this paper can reduce unnecessary movements and detours without compromising path feasibility. In contrast to the basic method of the MSF-MTPO algorithm, which mainly optimizes the neighborhood, the new TDO-MSF method takes into account directional constraints and deviation-aware neighbor selection when searching for the route.

3.3.2. Turn-deviation cost function

The cumulative turning penalty is calculated as:

$$P_{\text{turn}} = \sum_i \left(\frac{\theta_i}{180}\right)^2, \tag{4}$$

where θ_i denote the turning angle and is normalized by 180° to ensure numerical stability. Squaring the normalized turning angle imposes a greater penalty on directional changes, thereby helping achieve smoother trajectories. Traditional graph-based algorithms construct a graph representation of the environment and determine feasible paths through iterative node expansion. Recent studies have enhanced the conventional A* algorithm by incorporating bidirectional search, adaptive neighborhood expansion, and heuristic optimization to reduce computational complexity while improving path quality and reducing unnecessary turning maneuvers [1].

The path deviation cost can be expressed as:

$$D_{\text{dev}}(C) = \left|\phi_C - \phi_{\text{goal}}\right|, \tag{5}$$

where ϕ_C denotes the moving direction of the current node and ϕ_{goal} denotes the desired direction toward the target node.

By incorporating both turning and deviation penalties into the search process, the proposed evaluation function guides the bidirectional A* algorithm toward trajectories with fewer unnecessary turns, reduced path deviation, and improved navigation smoothness while preserving computational efficiency. Based on the parameter sensitivity analysis presented in Section 3.2.6, the weighting coefficients are selected as $\lambda = 50$ and $\mu = 20$, which provides the best trade-off among path optimality, trajectory smoothness and computational efficiency.

3.3.3. Node evaluation and path selection

The proposed TDO-MSF, with each node generated during the bidirectional search, is evaluated using a multi-criteria cost function that integrates path length, heuristic distance, turning penalty, and deviation penalty. The main difference from the current

Table 3: Sensitivity analysis of turn penalty (λ) and deviation penalty (μ) parameters.

λ	μ	Distance (m)	Number of Turns
20	10	28.40	5
30	15	28.10	4
40	20	27.95	3
50	20	27.90	2
60	25	28.20	2

A* algorithm employing $g(n) + h(n)$ is the presence of some special geometrical parts in the new algorithm

The overall node evaluation function is defined as

$$f(n) = g(n) + h(n) + \lambda N_{\text{turn}}(n) + \mu D_{\text{dev}}(n). \tag{6}$$

$g(n)$ represents the actual cost from the start node, $h(n)$ is the heuristic cost to the goal, $N_{\text{turn}}(n)$ denotes the accumulated turning cost and D_{dev} represents the deviation cost from the target direction. The parameters λ and μ are adjustment factors that control the influence of turning and deviation penalties, respectively.

During the search process, nodes with the minimum $f(n)$ value is selected from the priority queue for expansion, ensuring the algorithm prefers smoother, more directionally consistent paths over purely shortest geometric paths. Moreover, any nodes that violate the directionality requirements specified in Table 2 are pruned during expansion, thereby avoiding needless branching. This approach to evaluating nodes enables the developed model to produce trajectories with less turning and smoother paths than conventional MSF-MTPO and ordinary A* methods.

3.3.4. Novelty of the proposed search strategy

Unlike the MSF-MTPO technique, this approach, the TDO-MSF technique, along with the traditional path cost and heuristic function, also accounts for the effects of turning and path deviation when computing paths. The node evaluation mechanism incorporates directional constraints, turn penalties and deviation penalties, enabling the search to generate smoother and more UAV-feasible trajectories.

Furthermore, the direction restriction neighbor expansion technique ensures that no unnecessary node expansion or direction change takes place during the formation of the route. As a result, the resulting path requires fewer modifications during the smoothing phase. Consequently, the proposed search strategy produces shorter, smoother and more stable trajectories than conventional neighborhood-based path-planning methods.

3.3.5. Search process summary

The newly proposed turn-deviation-optimized bidirectional A* algorithm begins by exploring nodes adjacent to one another in accordance with specified directional constraints. This node, which gives the minimum evaluation cost, is selected from the list of candidate nodes using the turn-deviation cost function. Both searches run in parallel until a connection is established between them, thereby forming a preliminary non-colliding path with minimal turns and path-deviating behaviors. The resulting collision-free path is further optimized during the inflection correction phase.

3.3.6. Parameter sensitivity analysis

The weighting factors λ and μ control the relative importance of turning behavior and path deviation during the bidirectional A* search process. To determine appropriate parameter values, a sensitivity analysis was performed over multiple combinations of $\lambda \in \{10, 20, 30, 40, 50, 60\}$ and $\mu \in \{5, 10, 15, 20, 25, 30\}$. For each parameter pair, the presented TDO-MSF approach was evaluated in benchmark environments with respect to path length, number of turns, and computational efficiency. As the experiments show, smaller λ values lead to shorter paths, yet they still involve many unnecessary turns. Otherwise, for large λ, there will be an increase in computational time and unnecessary deviations in paths. The same applies to μ values – small μ allows for deviation, while large values prevent efficient path exploration and optimization. This set of parameters, $\lambda = 50$ and $\mu = 20$, appears to be the best choice when considering all efficiency opportunities and computational cost.

Table 3 clearly indicates that the values λ=50 and μ=20 yield the best compromise between trajectory length and turn minimization, which justifies their use in the suggested TDO-MSF approach.

3.3.7. Multi-scale inflection correction

The first path found via the turn-deviation bidirectional A* algorithm with optimization can contain many unnecessary inflection points, since its discrete grid representation is explicit. Unnecessary inflections add Excessive maneuverability and affect the simplicity of the resulting path. Thus, the multiscale correction-of-inflections method is applied.

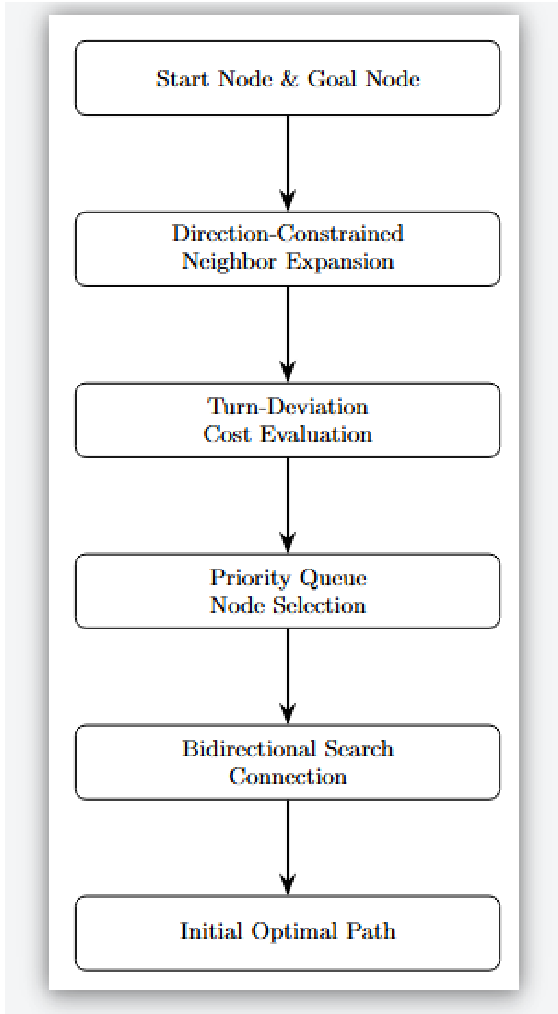

Figure 5: Workflow of the proposed turn-deviation search strategy.

The total turning angle of the path is given by

$$\Theta_{\text{total}} = \sum_{k=1}^{n-1} \theta_k, \tag{7}$$

where θ_k denotes the turning angle at the waypoint.

Turning behavior is modelled based on different levels of neighborhoods (3,7,5), in case the turning angle at a waypoint is smaller than the threshold value, and the straight line between the consecutive waypoints. If the waypoints encounter no obstacles, the corresponding inflection point is ignored. In that case, the actual waypoint will be preserved to ensure safety while path planning.

The proposed multi-scale algorithm is advantageous over the classical single-scale algorithm in detecting inflection points. As a result, the corrected trajectory contains fewer redundant turning points while maintaining obstacle clearance.

The optimized waypoint sequence obtained from this stage is subsequently used as the input to the curvature-constrained adaptive smoothing module.

The initial path generated by the four-neighborhood search contains several redundant inflection points due to grid discretization. The proposed multi-scale inflection correction strategy removes unnecessary intermediate turning points by directly connecting feasible waypoints while preserving collision avoidance constraints. As a result, the generated trajectory becomes smoother and more suitable for UAV navigation.

For instance, the four-neighborhood A* algorithm produces an initial path that contains several axis-aligned line segments, thus creating several inflection points, see Figure 6.

However, in practice, a UAV may not necessarily visit all intermediate inflection points in sequence. When there are no obstacles between two disconnected points, the UAV may skip several intermediate inflection points in favor of a direct connection. It means there is marked redundancy in the path generated by conventional algorithms due to an excessive number of turning points.

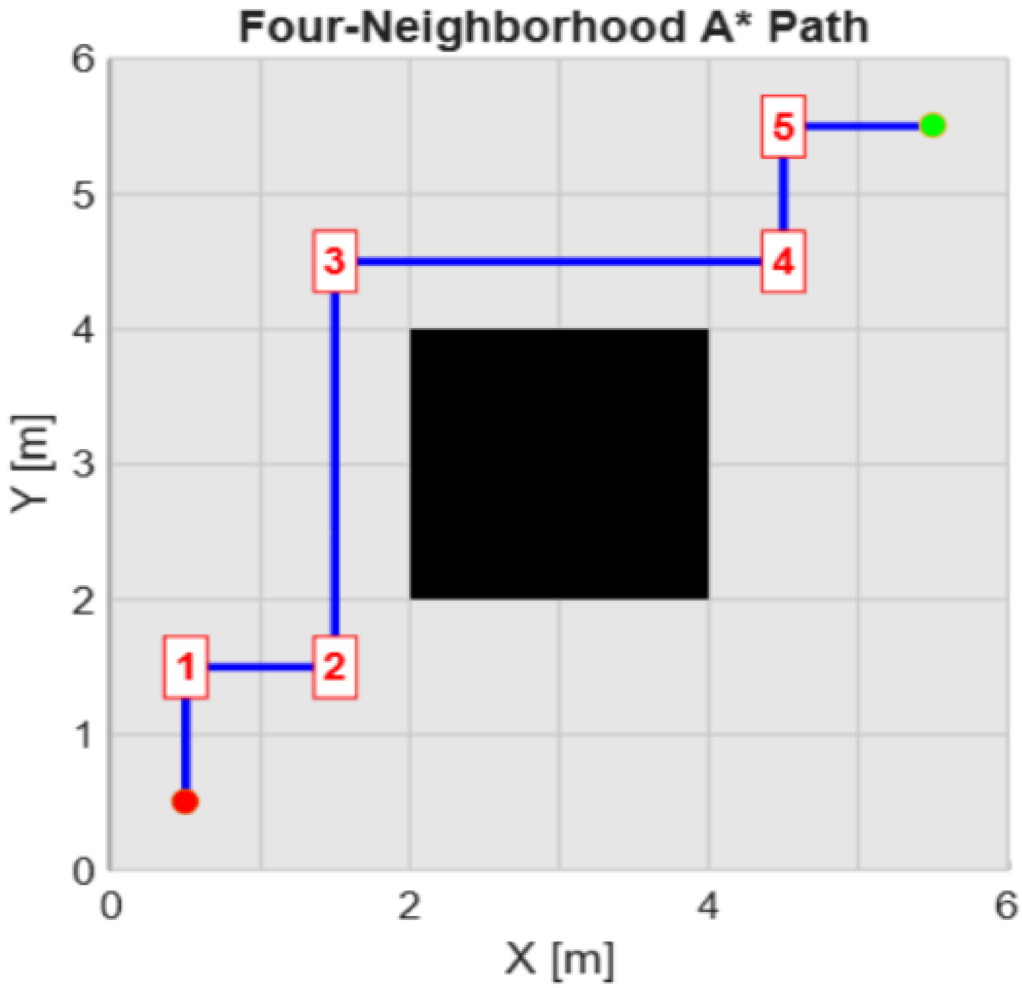

Figure 6: Four-neighborhood search trajectory.

To overcome the drawbacks of the standard method, the proposed TDO-MSF employs an advanced inflection-point correction algorithm. In contrast to the baseline conventional method, which considers only the presence of obstacles to establish a connection between two nodes, the new technique also considers the feasibility and orientation of the connection. Turning points are determined by the change in orientation, and the connection is made directly when no obstacles are present between two disconnected points.

3.4. *Curvature-constrained adaptive-radius smoothing*

3.4.1. *Motivation*

While the inflection correction phase can filter out unnecessary points, abrupt turns may still occur due to the discretization inherent in trajectory planning. These abrupt turning points may be against the constraints of UAV maneuverability and limit its flight stability. To overcome this issue, the TDO-MSF approach employs an adaptive curvature-radius smoothing algorithm to generate a smooth flight path. While other techniques used throughout the world, such as the Bezier curve-fitting technique and spline interpolation, tend to alter the original shape of the path, this technique ensures that local smoothing occurs only at points of inflection.

3 sequential path points, P_1, P_2 and P_3 are selected, with being the inflection point. The turning angle θ is estimated using two vectors and If the turning angle exceeds a certain limit, the sharp bend is replaced with an arc.

3.4.2. *Adaptive turning radius*

The adaptive turning radius is computed as

$$r = \frac{k\theta}{2\sin(\theta/2)} R_{\min}, \tag{8}$$

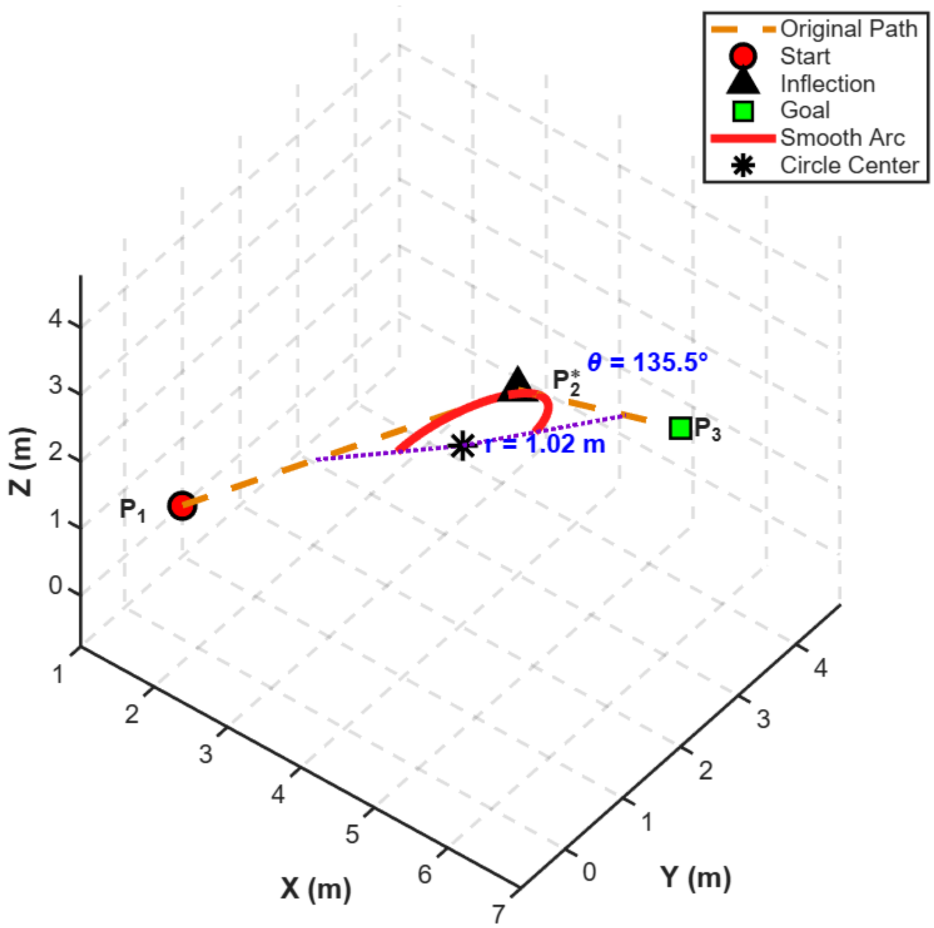

Figure 7: Adaptive radius-based trajectory smoothing.

where k is the scale factor, θ is the turning angle, and R_{min} is the minimum turning radius of the UAV. It is obvious that as the turning angle increases, the radius increases; otherwise, it decreases.

3.4.3. UAV feasibility

The computed smoothing radius is further constrained to ensure practical flight feasibility by the UAV maneuverability requirement

$$r \geq \frac{v^2}{a_{\max}}, \tag{9}$$

where v is the UAV velocity and $a_{\max}$ is the maximum allowable acceleration.

3.4.4. Novelty of the proposed smoothing strategy

In contrast to the basic MSF-MTPO approach, which uses traditional trajectory optimization, the novel TDO-MSF algorithm employs a curvature-constrained smoothing process that accounts for the radius of curvature at each point in the path geometry and the UAV's dynamic constraints, thereby yielding more practical trajectories.

3.5. Trajectory-guided enhanced artificial potential field

Although the global path generated by the proposed TDO-MSF provides an optimized collision-free trajectory, unexpected dynamic obstacles may appear during UAV navigation. To improve local obstacle avoidance while preserving the quality of the global path, a trajectory-guided Enhanced Artificial Potential Field (E-APF) is introduced.

The attractive potential guiding the UAV toward the target is defined as

$$U_{\text{att}} = \frac{1}{2} k_a d_g^2, \tag{10}$$

where k_a is the attractive gain coefficient and d_g denotes the distance between the UAV and the target position.

The repulsive potential generated by nearby obstacles is expressed as:

$$U_{\text{rep}} = \begin{cases} \frac{1}{2} k_r \left(\frac{1}{d_o} - \frac{1}{d_0} \right)^2, & d_o < d_0, \\ 0, & d_o \geq d_0, \end{cases} \tag{11}$$

where k_r is the repulsive gain coefficient, d_o represents the distance between the UAV and the obstacle, and d_0 is the obstacle influence distance.

To reduce local minima and unnecessary path deviation, a trajectory-guidance potential is incorporated as:

$$U_{\text{guide}} = k_g d_p^2, \tag{12}$$

where is k_g the guidance coefficient and d_p denotes the distance between the UAV and the optimized TDO-MSF trajectory.

The total potential field is therefore computed as

$$U_{\text{total}} = U_{\text{att}} + U_{\text{rep}} + U_{\text{guide}}, \tag{13}$$

and the resultant navigation force acting on the UAV is obtained from the negative gradient of the total potential field:

$$F = -\nabla U_{\text{total}}. \tag{14}$$

Compared with other methodologies for solving the APF problem for UAVs, the proposed methodology consistently seeks to optimize the UAV's path by guiding it along the optimal trajectory while avoiding dynamic obstacles. The collision-free optimized trajectory calculated by the E-APF model is then validated against UAV dynamic constraints.

3.6. *UAV dynamic feasibility verification*

The optimized path calculated by the developed TDO-MSF algorithm must comply with the dynamic constraints of UAV operation. Dynamic constraints to consider include velocity, acceleration, jerk and turn radius.

The velocity of the UAV is evaluated by

$$v_i = \frac{\|P_{i+1} - P_i\|}{\Delta t}, \tag{15}$$

where P_i represents the UAV position and Δt is the sampling interval.

The acceleration is evaluated by

$$a_i = \frac{v_{i+1} - v_i}{\Delta t}, \tag{16}$$

while the jerk is obtained as

$$j_i = \frac{a_{i+1} - a_i}{\Delta t}. \tag{17}$$

The trajectory must satisfy

$$v_i \leq v_{\max}, \quad a_i \leq a_{\max}, \quad j_i \leq j_{\max}. \tag{18}$$

Furthermore, the requirement for minimum turning radius is tested by

$$r \geq \frac{v^2}{a_{\max}}. \tag{19}$$

The path planning is again validated using the criteria of smoothness, average curvature, and energy to confirm the generation of feasible UAV paths. Unlike most current algorithms, which mainly focus on optimizing path geometry length, the developed approach incorporates the validation of UAV dynamic feasibility.

The dynamically feasible trajectory obtained at this stage is subsequently analyzed for computational complexity and experimentally evaluated.

3.7. *Computational complexity analysis*

The computational complexity of the proposed TDO-MSF is determined by the bidirectional A* search, multi-scale inflection correction, adaptive smoothing, and dynamic obstacle avoidance stages.

*3.7.1. Complexity of conventional A**

Let b denotes the branching factor and d denotes the search depth. In the worst case, conventional A* expands $O(b^d)$ nodes. Since node insertion and extraction are performed using a priority queue, each operation requires $O(\log N)$ time, where N denotes the number of generated nodes. Therefore, the worst-case time complexity of A* is

$$T_{A^*} = O(b^d \log N), \tag{20}$$

and the corresponding space complexity is

$$S_{A^*} = O(N), \tag{21}$$

since all generated nodes may need to be stored in the open and closed lists.

*3.7.2. Complexity of bidirectional A**

Bidirectional A* simultaneously performs forward and backward searches from the start and goal nodes. Assuming that both searches progress approximately to depth $d/2$, the number of explored nodes becomes

$$O(b^{d/2}), \tag{22}$$

for each search direction. Considering the priority queue operations, the overall time complexity becomes

$$T_{\mathrm{BiA}^*} = O(b^{d/2} \log N), \tag{23}$$

while the corresponding space complexity remains

$$S_{\mathrm{BiA}^*} = O(N). \tag{24}$$

3.7.3. Complexity of the proposed TDO-MSF

The Multi-Scale Inflection Correction (MSIC) stage processes each trajectory waypoint only once and therefore has a linear time complexity of $O(n)$, where n denotes the number of trajectory waypoints. Similarly, the Curvature-Constrained Adaptive Radius Smoothing (CCARS) stage performs a single traversal of the waypoint sequence and also incurs a time complexity of $O(n)$. The Trajectory-Guided Enhanced Artificial Potential Field (TG-EAPF) stage evaluates local obstacle interactions along the trajectory and likewise exhibits a linear time complexity of $O(n)$.

As a result, the additional processing stages introduced by the proposed TDO-MSF contribute only linear computational overhead. The overall time complexity of the framework can thus be expressed as

$$T_{\text{TDO-MSF}} = O(b^{d/2} \log N + n), \tag{25}$$

where b denotes the branching factor, d represents the search depth, N is the number of explored nodes, n and is the number of trajectory waypoints. The corresponding space complexity is

$$S_{\text{TDO-MSF}} = O(N). \tag{26}$$

Although the proposed framework introduces additional optimization stages compared with MSF-MTPO, these operations are performed locally and therefore do not increase the overall computational complexity. The complexity analysis demonstrates that the proposed TDO-MSF framework maintains the computational efficiency of the bidirectional A algorithm while improving trajectory quality, reducing unnecessary turning maneuvers and enhancing UAV dynamic feasibility.

3.8. Comparative analysis of MSF-MTPO and the proposed TDO-MSF

The proposed TDO-MSF can be regarded as an enhanced version of the conventional MSF-MTPO method, developed through several optimization stages. Both schemes use a two-way search algorithm and multistage trajectory optimization; however, there are differences, as the TDO-MSF method incorporates improvements in trajectory optimization and UAV flight feasibility. Unlike the MSF-MTPO technique, which does not account for heading-angle deviations when defining the cost function, the TDO-MSF scheme uses a deviation-oriented cost function for heading angles. Additionally, a multi-scale inflection-point detection approach is used to improve the accuracy of turning-point selection. The proposed TDO-MSF employs curvature-constrained adaptive trajectory smoothing, allowing turning radii to vary based on local path features and the constraints imposed by UAV maneuvers. Finally, an enhanced Artificial Potential Fields-based trajectory guidance is used to improve dynamic obstacle avoidance.

To make practical use of such trajectories, their validation is performed according to UAV dynamics constraints such as velocity, acceleration, jerk, and turning radius. The cost in terms of energy and smoothness is also considered when evaluating the resulting trajectories. Even though this new framework adds more optimization steps, they are local processes and do not increase the problem's computational complexity.

Table 4 Highlights the principal differences between the baseline MSF-MTPO algorithm and the proposed TDO-MSF. By incorporating turn and deviation optimization, adaptive smoothing, trajectory-guided obstacle avoidance, and UAV dynamic verification, the proposed framework generates smoother, more feasible trajectories while maintaining computational efficiency.

Table 4: Comparative analysis of MSF-MTPO and the proposed TDO-MSF.

Feature	MSF-MTPO	Proposed TDO-MSF
Bidirectional A*	✓	✓
Turn penalty	×	✓
Deviation penalty	×	✓
Multi-scale inflection correction	×	✓
Adaptive-radius smoothing	Fixed	Adaptive
Trajectory-guided E-APF	×	✓
UAV dynamic verification	×	✓
Energy cost evaluation	×	✓

Table 5: Benchmark UAV navigation environments used for performance evaluation.

Map	Environment Type	Obstacle Density	Complexity
Map1	Sparse Environment	Low	Simple
Map2	Moderate Environment	Medium	Moderate
Map3	Dense Environment	High	Complex
Map4	Corridor Environment	Medium	Moderate
Map5	Cluttered Environment	High	Complex
Map6	Dynamic Obstacle Environment	Variable	Very Complex

4. Experimental configuration and results

4.1. Simulation environment

The simulation was conducted using MATLAB R2023a on the MATLAB Online platform, which offers a cloud computing solution. Despite the computations being performed remotely, the performance is similar to that of a conventional desktop computer. All simulations were conducted under consistent settings to ensure a fair comparison between the baseline MSF-MTPO algorithm and the proposed TDO-MSF. The use of an online platform also enhances reproducibility and accessibility of the experimental setup. The computational environment is abstracted by the MATLAB Online platform, which dynamically allocates system resources. Thus, the performance assessment relies on comparative evaluation rather than hardware-specific measures. The suggested approach is not hardware-specific and can be implemented either locally or on cloud computing infrastructure.

4.2. Benchmark environments

Table 5 benchmark environments were designed to evaluate algorithm performance under progressively increasing navigation difficulty. Map1 and Map2 represent relatively simple environments with fewer obstacles, whereas Map3–Map5 contain denser obstacle distributions and more challenging path-planning conditions. Map6 further introduces dynamic obstacle interactions, allowing assessment of real-time obstacle-avoidance capabilities. The use of multiple benchmark environments improves the robustness and generalizability of the experimental evaluation.

4.3. Comparative algorithms

The effectiveness of the proposed TDO-MSF framework is evaluated through comparisons with several representative UAV path-planning algorithms, including the conventional A* algorithm, the Improved A* algorithm [12], the Improved Crow Search Sparrow Algorithm (ICSSA) [33], the Improved Rapidly-exploring Random Tree (Improved RRT) algorithm [14], the Improved Particle Swarm Optimization (Improved PSO) algorithm [37] and the baseline MSF-MTPO algorithm [1]. The trajectory-planning performance of each algorithm is evaluated using multiple benchmark environments with different obstacle densities and navigation complexities. To ensure a fair comparison, all algorithms are implemented using the parameter settings and simulation configurations recommended in their respective publications.

4.3.1. Stationary scene 1

Three cases are designed to test the suggested method in a 3D environment of size 20×20×20. The first case involves a specially designed map with obstacles, while Maps 2 and 3 are random maps with 100 obstacles each. The obstacle elevation across all scenarios is randomly determined. The drone is initialized at (2, 2, 3) while its destination is (19, 19, 10). The proposed algorithm is used for path search, with path-cost coefficients set to 0.25.

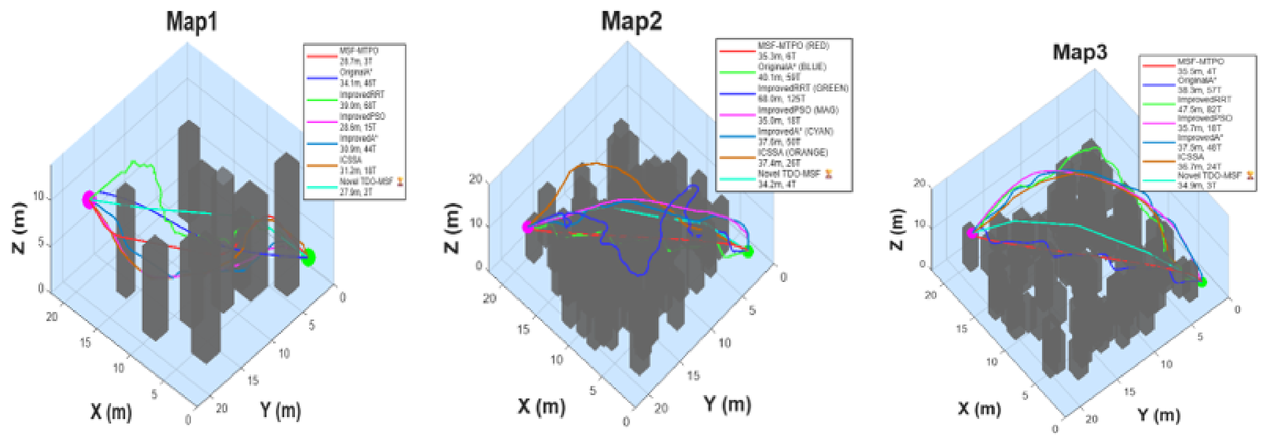

Figure 8: Comparison of trajectories generated by different algorithms in Stationary scene 1.

Table 6: Comparative analysis of algorithms across diverse map environments.

Map	Algorithm	Total Turning Angle (°)	Time (s)	Distance (m)	Number of Turns	Min Dist. Obstacle (m)	Smooth	Path Cost	Avg. Curvature (1/m)	Energy Cost	Smoothness Index
Map1	TDO-MSF	180.00	0.40	27.90	02	1.80	Yes	0.070	0.065	15.20	0.847
	MSF-MTPO	181.53	0.42	28.71	03	1.68	Yes	0.071	0.082	18.60	0.791
	Original A*	711.04	0.31	34.10	46	1.14	Yes	0.107	0.410	96.50	0.321
	Improved A*	606.58	4.04	30.94	44	1.96	Yes	0.086	0.356	84.10	0.371
	Improved RRT	3329.52	0.09	39.94	68	1.52	No	0.202	0.921	285.40	0.107
	Improved PSO	247.65	4.96	28.55	15	1.59	No	0.077	0.143	26.80	0.694
	ICSSA	402.56	0.72	31.23	18	1.17	No	0.091	0.225	44.70	0.573
Map2	TDO-MSF	360.00	0.52	34.20	04	1.85	Yes	0.075	0.092	28.50	0.765
	MSF-MTPO	1179.68	1.99	35.31	06	1.22	Yes	0.100	0.278	115.20	0.412
	Original A*	896.14	2.75	40.11	59	1.43	Yes	0.101	0.517	143.40	0.281
	Improved A*	699.44	3.80	37.60	50	1.49	Yes	0.093	0.391	104.80	0.362
	Improved RRT	5875.30	0.23	68.00	125	1.57	No	0.228	1.338	524.30	0.061
	Improved PSO	243.48	4.31	34.99	18	0.78	No	0.102	0.136	25.60	0.711
	ICSSA	540.94	2.20	37.44	26	1.67	No	0.087	0.295	72.30	0.468
Map3	TDO-MSF	270.00	0.48	34.90	03	1.82	Yes	0.073	0.078	21.70	0.801
	MSF-MTPO	218.87	1.71	35.54	04	0.95	Yes	0.086	0.095	24.80	0.755
	Original A*	807.60	2.67	38.29	57	1.38	Yes	0.103	0.462	128.60	0.297
	Improved A*	688.68	3.66	37.53	48	1.30	Yes	0.101	0.382	103.90	0.355
	Improved RRT	3698.96	0.11	47.50	82	1.56	No	0.194	0.948	302.70	0.098
	Improved PSO	214.85	4.21	35.74	18	1.11	No	0.089	0.127	24.10	0.726
	ICSSA	536.88	2.33	36.74	24	1.32	No	0.094	0.281	69.50	0.486

4.3.2. Stationary scene 2

To further evaluate the proposed method, three scenarios are implemented on a 50×50×20 3D environment. Maps Four, Five, and Six consist of 500 stochastically distributed obstacles, with obstacle heights generated probabilistically. The initial and target positions of the drone are defined as (2, 2, 3) and (49, 49, 15), respectively.

By incorporating the multi-scale inflection correction and turn-aware optimization strategy, the proposed TDO-MSF algorithm mainly reduces the number of trajectory inflection points compared with existing methods. The experimental findings based on six different scenarios using maps prove that the approach suggested is effective as it has been able to decrease the turning point values by about 29.25%, 94.52%, 93.94%, 98.11%, 90.35% and 92.25% when compared with MSF-MTPO, Original A*, Improved A*, Improved RRT, Improved PSO and ICSSA, respectively.

As shown in Table 7, the proposed method effectively eliminates unnecessary directional changes, thereby ensuring smoother flight trajectories.

In addition to reducing trajectory inflection points, the proposed TDO-MSF algorithm also achieves consistent improvements in path length across multiple environments. Our empirical results for six maps demonstrate that the new approach reduces the distance by about 3.11%, 12.05%, 9.12%, 38.22%, 5.08%, and 10.42% compared with MSF-MTPO, Original A*, Improved A*, Improved RRT, Improved PSO, and ICSSA, respectively. Although the percentage gain in distance compared to the original algorithm seems small, MSF-MTPO greatly reduces the number of turns in the new approach, confirming its effectiveness. This twofold optimization

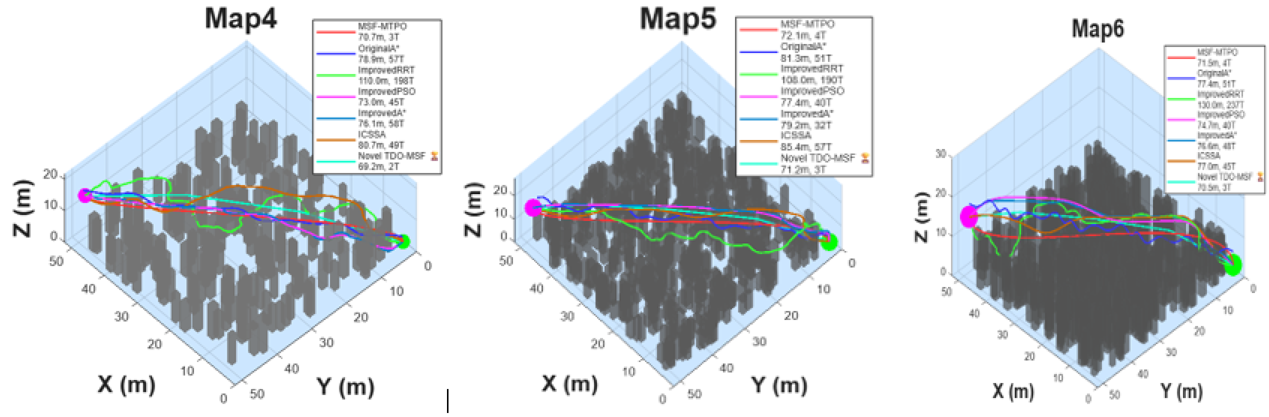

Figure 9: Comparison of trajectories generated by different algorithms in Stationary scene 2.

Table 7: Comparative analysis of algorithms across diverse map environments.

Map	Algorithm	Total Turning Angle (°)	Time (s)	Distance (m)	Number of Turns	Min Dist. Obstacle (m)	Smooth	Path Cost	Avg. Curvature (1/m)	Energy Cost	Smoothness Index
Map4	TDO-MSF	180.00	0.90	69.20	02	1.90	Yes	0.082	0.028	15.00	0.847
	MSF-MTPO	63.54	6.40	70.68	03	1.04	Yes	0.063	0.012	4.80	0.919
	Original A*	1201.39	23.16	78.94	57	1.51	Yes	0.098	0.267	185.40	0.230
	Improved A*	1260.09	132.24	76.10	58	1.30	Yes	0.102	0.289	196.70	0.219
	Improved RRT	8846.73	1.69	110.00	198	1.54	No	0.224	1.406	740.50	0.039
	Improved PSO	793.23	142.12	72.95	45	1.34	No	0.094	0.189	118.20	0.312
	ICSSA	1198.56	8.70	80.73	49	1.84	No	0.095	0.254	181.30	0.233
Map5	TDO-MSF	270.00	0.95	71.20	03	1.88	Yes	0.084	0.039	23.50	0.801
	MSF-MTPO	69.21	7.77	72.07	04	1.72	Yes	0.062	0.014	5.70	0.906
	Original A*	1053.61	36.73	81.27	51	1.03	Yes	0.103	0.227	162.40	0.255
	Improved A*	686.06	136.47	79.19	32	1.44	Yes	0.089	0.137	96.50	0.369
	Improved RRT	8253.10	0.58	108.00	190	1.56	No	0.225	1.334	701.80	0.042
	Improved PSO	527.05	159.85	77.43	40	1.37	No	0.086	0.114	62.40	0.517
	ICSSA	1345.55	9.24	85.38	57	1.24	No	0.104	0.276	214.8	0.206
Map6	TDO-MSF	270.00	0.92	70.50	03	1.90	Yes	0.083	0.041	23.10	0.801
	MSF-MTPO	128.81	8.15	71.52	04	1.57	Yes	0.077	0.026	11.30	0.847
	Original A*	1066.43	38.70	77.40	50	1.82	Yes	0.089	0.240	165.10	0.252
	Improved A*	1059.11	153.44	76.64	48	1.56	Yes	0.092	0.228	161.80	0.255
	Improved RRT	10186.33	4.92	130.00	237	1.54	No	0.249	1.368	852.60	0.034
	Improved PSO	548.74	153.11	74.74	40	0.77	No	0.105	0.122	68.70	0.499
	ICSSA	933.58	9.10	77.00	45	1.54	No	0.088	0.205	138.4	0.278

demonstrates the superior performance of the TDO-MSF in delivering efficient, dynamically feasible UAV trajectories in complex three-dimensional environments.

Figure 10 illustrates the dynamic trajectory planning results of the proposed TDO-MSF framework in a three-dimensional environment containing static obstacles. The figure presents both the planned trajectory and the actual UAV trajectory, demonstrating that the proposed framework achieves collision-free navigation while maintaining path optimality.

In Figure 10, the orange curve represents the planned resulting trajectory by the TDO-MSF algorithm under static conditions. This trajectory is obtained through turn-penalized bidirectional A* search, followed by multi-scale inflection correction and adaptive radius-based smoothing. As a result, the planned path exhibits fewer directional changes and greater smoothness than conventional methods.

The red curve indicates the actual path of the UAV during navigation in the presence of dynamic disturbances. The UAV begins to follow the planned trajectory very precisely at the start. But when the UAV approaches the area with dynamic obstacles (marked with a black point), it tends to deviate from the planned trajectory for safety reasons. This is because the E-APF method considers both global optimal navigation and avoidance of dynamic obstacles.

Unlike other methods that use APF, the UAV trajectory in this paper will not deviate much from the global optimal trajectory. After successfully avoiding the obstacle, the UAV slowly returns to its course until it reaches its destination. It shows that the constrained potential term of the trajectory is effective at guiding the global optimal trajectory.

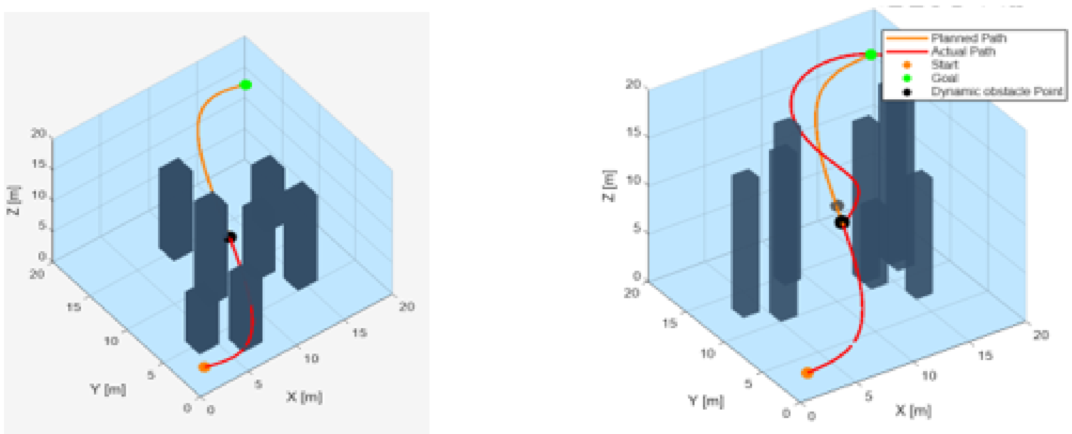

Figure 10: TDO dynamic path path trajectory.

Finally, the trajectory remains smooth throughout the planning process. As shown in Figure 10, the proposed TDO-MSF framework achieves an effective balance among path optimization, obstacle avoidance and trajectory smoothness, which are essential for safe and efficient UAV navigation.

4.4. Evaluation metrics

A variety of performance metrics have been adopted to assess the efficacy of the TDO-MSF scheme for UAV path planning. In contrast with traditional approaches based on metrics such as path length and computation time, the evaluation metrics adopted in this work also take into account factors such as trajectory quality, maneuverability and flight feasibility.

4.4.1. Total turning angle (degree)

The total turning angle is the sum of all local turning angles during trajectory generation. It is better to have a small total turning angle when creating smooth trajectories.

4.4.2. Number of turns

The number of turns refers to the number of times the UAV's path direction has been changed during its movement or planning. The fewer the turns, the more stable the UAV's path will be, and the less energy will be required.

4.4.3. Distance to obstacles (meters)

Distance to obstacles is the shortest distance from any obstacle to the path planned by the UAV.

4.4.4. Trajectory smoothness

Trajectory smoothness ensures that the generated trajectory is practical, as it contains no sudden turns or abrupt changes.

4.4.5. Path cost

Path cost is a measure of how optimized the path obtained from a path planning process is.

4.4.6. Average curvature (1/m)

The average curvature refers to the total curvature of the planned route. A lower curvature value implies a smoother, more maneuverable path of flight.

4.4.7. Energy consumption

Energy consumption reflects the amount of energy required for the UAV to fly along the planned route. This measure is affected by the total distance flown, turning actions, and smoothness of the whole path.

Table 8: Ablation study of the proposed TDO-MSF.

Model	Distance (m)	Turns	Avg Curvature (1/m)	Energy Cost	Smoothness Index
Bidirectional A*	29.80	7	0.135	32.6	0.652
+ Turn-Deviation Cost	28.70	5	0.112	26.4	0.718
+ Multi-Scale Correction	28.10	4	0.094	22.8	0.772
+ Adaptive Smoothing	27.95	3	0.082	19.3	0.804
+ Enhanced APF	27.92	3	0.073	17.5	0.828
Full TDO-MSF	27.90	2	0.065	15.2	0.847

4.4.8. Smoothness index

The smoothness index is a normalized quantitative indicator used to evaluate trajectory continuity. Higher smoothness index values indicate smoother, more dynamically feasible trajectories for UAV navigation.

To provide a more comprehensive assessment of UAV path-planning performance, this study includes additional trajectory-quality metrics: Average Curvature, Energy Cost, and Smoothness Index. While conventional metrics such as path length and computation time evaluate optimization efficiency, these additional indicators quantitatively measure trajectory continuity, maneuverability, and flight feasibility. Therefore, the proposed evaluation framework enables a more thorough comparison between the TDO-MSF and existing path-planning algorithms.

These evaluation metrics are employed throughout the experimental study to compare the proposed TDO-MSF with the Original A, Improved A, Improved RRT, Improved PSO, ICSSA and the baseline MSF-MTPO algorithms across different benchmark environments.

4.5. Ablation study

To investigate the contribution of each component of the proposed TDO-MSF, an ablation study was conducted by progressively enabling different modules of the algorithm. The evaluation was performed using the same benchmark environments and simulation settings adopted throughout this study.

The following configurations were considered:

Model A: Bidirectional A* Search

Model B: Model A + Turn-Deviation Cost Function

Model C: Model B + Multi-Scale Inflection Correction

Model D: Model C + Curvature-Constrained Adaptive Radius Smoothing

Model E: Model D + Trajectory-Guided Enhanced APF

Full TDO-MSF: Model E + UAV Dynamic Feasibility Verification

The experimental results demonstrate that the turn-deviation cost function significantly reduces unnecessary turning behavior, while the multi-scale inflection correction further removes redundant waypoints. Adaptive radius smoothing makes the trajectories more continuous, while the improved APF improves obstacle-avoidance performance. Lastly, the dynamic feasibility validation process guarantees that the generated trajectory meets the UAV's motion constraints. Overall, the TDO-MSF system achieves the optimal balance between path-length minimization and smoothness.

Table 8 provides the evidence from the ablation analysis shows that each component brings value to the overall system performance. For instance, the turn deviation cost function focuses on limiting excessive turns; the multi-scale inflection correction removes extra waypoints; the radius adaptation improves trajectory continuity; the improved APF increases safety; and dynamic feasibility checks make the UAV more maneuverable.

5. Comparative analysis

The performance of the developed TDO-MSF approach is analyzed through simulation experiments and compared with Original A*, Improved A*, Improved RRT, Improved PSO, ICSSA, and baseline MSF-MTPO approaches across various criteria, including path optimality, trajectory smoothness, obstacle avoidance, time consumption, and the dynamic feasibility of the UAV.

5.1. Qualitative performance

TDO-MSF is compared with other driving algorithms in the visual analysis based on their trajectories across various benchmark environments. The simulation results show that the traditional A* path planner produces trajectories with several unnecessary turns due to the grid-based path-construction technique. Even though improved A* and ICSSA algorithms minimize unnecessary turns, the geometrical shape of their paths is still quite irregular. The improved RRT algorithm exhibits good capability in exploring space but generates very uneven paths that require further processing.

However, the TDO-MSF method produces smoother and more compact paths through turn-deviation optimization, multi-scale inflection smoothing, radius-based adaptive smoothing, and trajectory-guided obstacle avoidance. The resulting trajectories have fewer turning points and greater safety when avoiding obstacles than those of previous methods. Thus, the proposed method is more suitable for UAV navigation applications.

5.2. Quantitative performance

Tables 6 and 7 present a numerical performance comparison between the proposed TDO-MSF method and existing UAV path-planning approaches. There are several indicators for measuring performance, including total turning angle, computation time, trajectory length, turning times, minimum obstacle clearance, trajectory cost, average trajectory curvature, energy consumption, and trajectory smoothness.

Tables 6 and 7 show that the proposed TDO-MSF method has advantages in terms of total turning angle, trajectory smoothness and computational efficiency while maintaining competitive path quality. Similar to recent multi-objective UAV path-planning approaches, the proposed framework simultaneously considers multiple performance criteria; however, it further incorporates turn-deviation optimization and dynamic feasibility verification to improve overall trajectory quality practical flight feasibility [38]. The proposed method aims to eliminate unnecessary paths while keeping better maneuverability.

5.3. Trajectory smoothness analysis

Trajectory smoothness is widely recognized as an important criterion in autonomous vehicle motion planning because excessive turning maneuvers reduce motion stability and increase control effort [41]. Hence, average curvature, energy cost and smoothness index are utilized to quantify the performance of the UAV trajectory.

Based on the results of the experiment, the suggested adaptive radius smoothing approach appears very promising for minimizing the average curvature and increasing the smoothness index. Furthermore, reducing unnecessary turns to minimize energy costs.

5.4. Performance of obstacle avoidance

With the implementation of trajectory information, the E-APF will improve its ability to avoid obstacles. Compared with the conventional APF method, the proposed trajectory-guided E-APF significantly reduces the likelihood of the UAV becoming trapped in local minima. Experimental results demonstrate that the TDO-MSF algorithm maintains a greater distance from the barrier.

5.5. Computational efficiency analysis

However, due to the introduced calculations for evaluating turn deviation, correcting for multi-scale inflections, adaptively smoothing, and guided barrier avoidance, the additional computational overhead remains relatively small. A bidirectional search algorithm considerably reduces the number of expanded nodes, and additional processing stages require only linear computation along the constructed path. Thus, the proposed algorithm offers balanced performance in terms of computation efficiency and path quality.

5.6. Discussion

The results of the experiments show that the TDO-MSF algorithm proposed in the paper solves multiple problems associated with the current state-of-the-art UAV path-planning methods. Namely, the inclusion of turn-deviation optimization in the algorithm decreases unnecessary changes of direction. Multi-scale inflection correction improves the reliability of turning points, while adaptive-radius smoothing helps make trajectories more consistent and better suited to UAV maneuvers.

Trajectory-guided enhanced artificial potential field increases obstacle-avoidance capability and decreases the risk of getting stuck in local minima. Additional parameters such as average curvature, energy cost, and smoothness index used in the experiment further demonstrate the effectiveness of the algorithm.

6. Conclusion and future work

In this research paper, the Turn-Deviation Optimized Multi-Stage Framework (TDO-MSF) approach for UAV path planning was proposed to improve trajectory performance, safety and feasibility. The framework comprises a turn-deviation-optimized two-way A* algorithm, multi-scale inflection correction, curvature-constrained adaptive radius trajectory smoothing, an improved artificial potential field technique that uses trajectory information, and UAV dynamic feasibility validation. Unlike graph search algorithms, sampling-based and optimization approaches have shown great efficiency in minimizing unnecessary turns, reducing trajectory deviation, enhancing smoothness, and improving obstacle avoidance. The incorporation of parameters such as average curvature, energy cost, and smoothness index also enables calculation of the overall quality of the trajectory. Experiments across different scenarios indicate the high efficiency of the proposed approach in obtaining shorter, smoother trajectories. The comparative analysis of the new algorithm against the original A*, improved A*, improved RRT, improved PSO, ICSSA, and the basic MSF-MTPO method demonstrates its superiority in UAV path planning. Although the proposed technique increases the number of computations required and necessitates some tuning parameters, the added benefit of better UAV trajectories justifies the extra computational burden. Future research should focus on expanding the proposed method to dynamic environments and to multiple UAVs operating simultaneously in collaboration, using simulation software such as AirSim. Overall, the proposed TDO-MSF provides an effective and practical solution for generating safe, smooth, collision-free, and dynamically feasible UAV trajectories in complex navigation environments.

Data availability

The datasets generated and/or analyzed during the current study are publicly available in the GitHub repository developed for this work and can be accessed at https://github.com/uavstatic/TDO_MSF_Path_planning.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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